# AI AND ROBOTICS: REVOLUTIONIZING SOLAR ENERGY

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**Abstract**

As the global community intensifies efforts to address climate change, solar energy emerges as a vital component of the transition to sustainable energy systems. Despite its promise as a clean and renewable alternative to fossil fuels, the full potential of solar power remains constrained without the integration of advanced technologies such as AI and robotics. These innovations are increasingly instrumental in enhancing the efficiency, reliability, and scalability of solar energy systems. This study examines the role of AI and robotic systems across various applications, including accurate energy forecasting, performance optimization, and automated maintenance, in accelerating the deployment of solar technologies. By analyzing key implementations and assessing their environmental, economic, and social impacts, the study highlights the transformative potential of AI in advancing a more sustainable energy future.

*Keywords: artificial intelligence, robotics, solar PV, forecasting, fault detection, optimization*

## 1. Introduction

The urgent need to combat climate change has propelled renewable energy sources to the forefront of global energy strategies, with solar power standing out for its abundance, accessibility, and zero-emission potential during operation. As of 2025, solar photovoltaic (PV) installations have surpassed 1.6 terawatts globally, driven by falling costs and supportive policies. However, challenges such as intermittency, maintenance inefficiencies, and suboptimal performance persist, hindering the widespread adoption and integration into the grid. Traditional solar systems, reliant on manual operations and basic controls, often suffer from inaccuracies in energy prediction, high operational costs, and vulnerability to environmental factors such as dust accumulation and shading. In this context, the convergence of Artificial Intelligence (AI) and robotics presents a paradigm shift, enabling intelligent automation, data-driven decision-making, and adaptive mechanisms that directly address these limitations.

This paper examines how AI algorithms—ranging from machine learning models for predictive analytics to deep neural networks for image-based diagnostics—and robotic systems, including drones, automated cleaners, and precision manipulators —are transforming the solar energy landscape. By examining applications across forecasting, fault detection, optimization, and maintenance, it becomes clear how these technologies not only enhance system reliability and output but also contribute to broader sustainability goals. Drawing from recent advancements between 2017 and 2025, the review synthesizes evidence from peer-reviewed sources to evaluate implementations, case studies, and multifaceted impacts. Ultimately, it positions AI and robotics as essential enablers for scaling solar energy, paving the way for a resilient, low-carbon future while highlighting pathways to overcome deployment barriers. The structure proceeds with a detailed methodology, results from key implementations, case studies, impacts, comparative metrics, a discussion through critical evaluation and SWOT analysis, and concluding insights.

## 2. Methods

This study adopts a systematic literature review approach to explore the integration of AI and robotics in solar energy systems. The methodology involved a comprehensive search of peer-reviewed articles, conference papers, and book chapters published between 2017 and 2025, sourced from databases such as IEEE Xplore, ScienceDirect, Scopus, and Google Scholar. Keywords used in the search included combinations of “artificial intelligence,” “robotics,” “solar PV,” “forecasting,” “fault detection,” “optimization,” and “robotic maintenance.”


10.18086/swc.2025.03.01 Available at http://proceedings.ises.org

## 2.1 Inclusion criteria

The inclusion criteria focused on studies that demonstrated practical implementations, case studies, and impact analyses in solar energy applications, with an emphasis on recent advancements (2017-2025) to capture emerging technologies. Exclusion criteria omitted non-English publications, purely theoretical works without empirical validation, and studies unrelated to photovoltaic (PV) systems.

Related studies were selected after screening abstracts and full texts for relevance, quality, and novelty. The review synthesizes findings thematically, categorizing them into implementations, case studies, impacts, challenges, and discussions. Qualitative analysis was employed to evaluate the environmental, economic, and social benefits, while comparisons with traditional methods highlight the advantages and limitations of AI. No primary data collection or experiments were conducted; instead, the essay relies on secondary sources to provide a high-level overview and critical evaluation.

## 2.2 Key technical terms

The following definitions provide context for the technical discussions, ensuring accessibility for readers unfamiliar with AI methodologies.

LSTM (Long Short-Term Memory): A type of recurrent neural network (RNN) architecture designed to model sequential data and capture long-range dependencies. LSTMs are particularly effective for time-series forecasting, such as solar radiation prediction, by utilizing memory cells and gates (input, forget, and output) to selectively retain or discard information over time, thereby mitigating issues like vanishing gradients that are common in standard RNNs.

CNN (Convolutional Neural Network): A deep learning model specialized for processing grid-like data, such as images. CNNs use convolutional layers to extract features through filters, pooling layers to reduce dimensionality, and fully connected layers for classification. In solar applications, CNNs are utilized for fault detection in PV panels by analyzing visual data to identify defects, such as hot spots or cracks.
GAN (Generative Adversarial Network): A framework consisting of two neural networks—a generator that creates synthetic data and a discriminator that evaluates its authenticity—trained in an adversarial manner to improve each other. When combined with CNNs (CNN+GAN), this approach generates augmented datasets for training, enhancing fault diagnosis in PV systems by simulating defects under limited real data scenarios.

YOLOv8-CrucibleDefectNet: A customized object detection model based on YOLOv8 (You Only Look Once version 8), an efficient real-time detection framework that predicts bounding boxes and class probabilities in a single pass. The CrucibleDefectNet variant incorporates enhancements such as Wise-IoU (WIoU) loss functions and Convolutional Principal Component Analysis (CPCA) attention mechanisms to improve small-target detection accuracy, tailored explicitly for identifying defects in quartz crucibles used in solar panel production.

# 3. Results

## 3.1 AI and Robotic Applications in Solar Energy

### *3.1.1 Solar Radiation Forecasting*

AI and robotic systems address challenges in solar radiation forecasting by improving tracking precision and alignment in PV and concentrated solar power (CSP) systems, crucial for accurate energy yield predictions. Model predictive control (MPC) resolves position control issues in DC servo motors for PV panels, enabling dynamic adjustments to forecasted solar paths with zero overshoots and superior energy efficiency compared to PID controllers (Pandya *et al.*, 2025). Disturbance-observer-enhanced MPC counters environmental disturbances in robotic dust-cleaning arms, achieving high tracking accuracy over traditional methods (Tang *et al.*, 2023). Soft-robotic structures enable dual-axis tracking and load balancing, outperforming stationary or single-axis systems in aligning with predicted solar trajectories (Busby *et al.*, 2024). Hybrid neural networks combined with kinematics improve heliostat calibration in solar towers to <0.7 milliradian precision, surpassing rigid-body or standalone neural approaches (Pargmann *et al.*, 2023). AI models, such as Long Short-Term Memory (LSTM) networks, achieve forecast accuracies with an RMSE of 62 W/m² across 116 sites and 14.36% for 10-minute forecasts. However, errors rise to 159.75 W/m² for longer horizons (Hu *et al.*, 2025). Similarly, LSTM models reduce hourly prediction errors by 10% (Olcay *et al.*, 2024). Ensemble ML models from non-PV contexts (94% accuracy) suggest potential for enhanced PV forecasting (Hemal *et al.*, 2024). These advancements ensure grid stability and reduce reliance on fossil fuels (Sammar *et al.*, 2024).

#### *3.1.2 Fault Detection and Diagnosis*

AI and robotics address high-error manual inspections and costly operations and maintenance (O&M) in solar plants through vision-based automation and the use of UAVs. Deep learning with UAVs detects ball joint faults in parabolic-trough systems via image analysis, achieving lower failure rates than human labeling (Pérez-Cutiño *et al.*, 2024). Multi-rotor UAVs enhance inspection efficiency in offshore wind and solar setups, reducing downtime and costs compared to manual, sensor-based, or robotic alternatives (Zhang *et al.*, 2024). Hybrid neural networks with kinematics correct heliostat calibration errors with sub-milliradian accuracy, overcoming data limitations (Pargmann *et al.*, 2023). Machine learning and drones in CSP lower O&M costs, achieving a LCOE of $ 44–$ 85/MWh (Bernehed *et al.*, 2023). Vision-based segmentation (0.95 mIoU) outperforms alternatives, such as PPLiteSeg, for PV component diagnostics (Surya Prakash *et al.*, 2024). CNNs paired with GANs achieve 92% fault classification accuracy, reducing maintenance response time by 30% (Lu *et al.*, 2023), while AI-driven defect localization cuts costs by 15% (Ghahremani *et al.*, 2025). Ensemble models deliver 94% accuracy, surpassing single classifiers (Hemal *et al.*, 2024), enhancing diagnostic reliability (Balachandran *et al.*, 2024).

#### *3.1.3 Performance Optimization and Energy Storage*

AI and robotic systems address PV performance bottlenecks, such as partial shading, radiation vulnerability, and energy dependency, through reconfiguration, tracking, and sustainable powering. SuDoKu algorithms mitigate shading-induced losses, enhancing power output over static methods (Shrivastava *et al.*, 2024). Silicon PV for space-based solar power (SBSP) offers 10-year durability and scalable production at lower costs than III-V PV (Aponte *et al.*, 2024). MPC and soft robotics enable precise solar alignment, with MPC outperforming PID in constraint handling (Pandya *et al.*, 2025) and soft robotics excelling in elevation (Busby *et al.*, 2024). Solar-powered robotic arms (with 80% efficiency and a 7.5g lift) and assistive devices facilitate off-grid operations (Okokpujie *et al.*, 2024; Mizanoor Rahman, 2024). Multi-robot systems and E-Walkers ensure precise SPS assembly, surpassing the capabilities of single-robot methods (Wan *et al.*, 2024; Nair *et al.*, 2024). Neural networks and path planners optimize arm manipulability and grasping, transferable to PV handling (Khan *et al.*, 2025; Yin *et al.*, 2025). Hybrid AI models increase energy capture by 12% via optimized tilt angles (Gürfidan *et al.*, 2025), while AI with compressed air storage boosts output by 20% (Assareh *et al.*, 2025). Neural networks improve PCM-based PV systems by 18% (Li *et al.*, 2025). Solar-powered USVs extend mission reliability (Sotelo-Torres *et al.*, 2023), indirectly supporting storage by reducing grid dependency (Gul *et al.*, 2025).

#### *3.1.4 Robotic Maintenance and Monitoring*

Robotic and AI systems address dust accumulation, labor intensity, and scalability issues in PV maintenance by automating tasks such as cleaning, path planning, and assembly. LQR schemes ensure stable motion in dust-removal robots, outperforming conventional methods (Nguyen *et al.*, 2025). Robotic cleaners enable faster and more scalable cleaning for large-scale panels (Nagrale *et al.*, 2024). Semi-autonomous systems offer navigation accuracy of over 96% and a 75-minute operation time (Munasinghe *et al.*, 2024), mitigating up to 50% of soiling losses (Al Humairi *et al.*, 2023). MPC enhances arm trajectory accuracy in the presence of disturbances (Tang *et al.*, 2023). Additive manufacturing reduces labor requirements for thin-film panel assembly (Carr *et al.*, 2023). UAVs and drones minimize

O&M costs and errors in solar plants (Zhang *et al.*, 2024; Pérez-Cutiño *et al.*, 2024; Bernehed *et al.*, 2023). Multi-robots and E-Walkers manage SPS assembly complexities (Wan *et al.*, 2024; Nair *et al.*, 2024). Soft actuators (with a 455 load-to-weight ratio) and path planners ensure collision-free navigation (Ye *et al.*, 2024; Poorvik *et al.*, 2024). Drones equipped with computer vision reduce monitoring costs by 25% (Kumar *et al.*, 2018), and robotic cleaning increases energy production by 10% (Martinez-Gil *et al.*, 2025). Ensemble models achieve 94% accuracy in solar-powered systems (Hemal *et al.*, 2024), outperforming manual approaches (Nawab *et al.*, 2023).

## 3.2. Case Studies

The integration of robotics and AI in solar energy applications addresses critical challenges in PV systems and space-based solar power infrastructure. Five case studies highlight advancements in defect detection, soiling management, dust removal, lunar assembly, and shaded panel detection.

- Automated Defect Detection: Zhao *et al.* (2025) developed a YOLOv8-CrucibleDefectNet system equipped with a robotic arm and camera, achieving a 95.08% mAP0.5 (1.39% improvement over YOLOv8n) for quartz crucible defect detection, thereby enhancing solar cell quality through automated inspections.
- Soiling Management: Ahmed *et al.* (2025) used EANN and CNN in HALCON software for soiled PV panel classification (99.91% precision), optimizing robotic cleaning cycles and improving efficiency.
- Dust Removal: Nguyen *et al.* (2025) developed an LQR-controlled robotic system for effective dust removal, which effectively navigates panel gaps and outperforms traditional methods.
- Lunar Solar Assembly: Nunziante *et al.* (2025) developed a dual-arm robotic system for lunar panel assembly, achieving higher accuracy than manual methods via integrated vision and control.
- Shaded Panel Detection: Shanthi Kumar *et al.* (2025) combined a CNN with an Additional Hardware Module for real-time shaded panel detection, enabling remote bypassing and enhancing PV longevity.

These cases demonstrate superior efficiency, precision, and scalability over traditional methods, advancing sustainable solar solutions.

## 3.3 Impacts on Sustainable Solar Energy Penetration

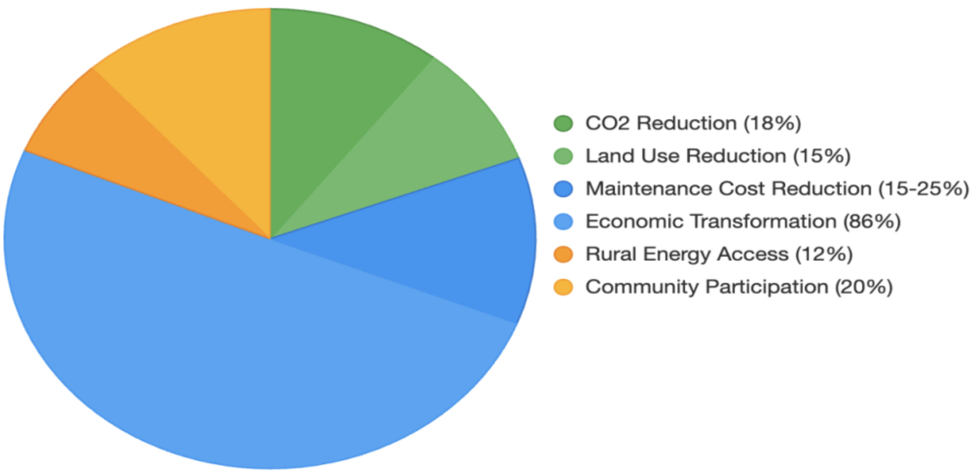


**Figure 1: Sustainability Impacts of AI and Robotics-Enhanced Solar PV Power**

### *3.3.1 Environmental Benefits*

AI-driven systems reduce carbon emissions by 18% in CSP systems (Gul et al., 2025) and cut land use by 15% in PV farms (Assareh et al., 2025), aligning with climate goals and surpassing traditional setups (Krishnan et al., 2023).

### *3.3.2 Economic Advantages*

AI reduces maintenance costs by 15% (Ghahremani et al., 2025) and monitoring costs by 25% through the use of drones (Kumar et al., 2018). By 2030, AI and robotics are expected to drive 86% of transformative economic impacts. However, 59% of the workforce will require retraining (WEF, 2025), making solar energy more affordable than conventional systems (Saleem and Abas, 2025).

### *3.3.3 Social Contributions*

AI improves rural energy access by 12% (Saleem and Abas, 2025) and boosts community participation by 20% through education programs (Mudassir et al., 2024), fostering equity over traditional approaches (Zhou et al., 2024).

## 3.4 Comparative Metrics

The following table summarizes key achievements across studies, categorized by application area, highlighting metrics and comparisons to traditional methods.

**Table 1: Achievements and Metrics of AI/Robotics in Solar PV**

| Category | Key Achievement/Metric | Comparison to Traditional Methods | Study |
|---|---|---|---|
| Solar Radiation Forecasting | Zero overshoots, superior energy efficiency in MPC for PV tracking | Outperforms PID in constraint handling and tracking | Pandya et al., 2025 |
| Solar Radiation Forecasting | High tracking accuracy with disturbance-observer MPC | More robust to disturbances than traditional controls | Tang et al., 2023 |
| Solar Radiation Forecasting | Effective dual-axis tracking and load balancing | Exceeds stationary/single-axis systems in energy production | Busby et al., 2024 |
| Solar Radiation Forecasting | <0.7 milliradian calibration precision | Surpasses rigid-body or standalone neural models | Pargmann et al., 2023 |
| Solar Radiation Forecasting | RMSE 62 W/m² over 116 sites, 14.36% for 10-min forecasts | Improves short-term accuracy for grid stability | Hu et al., 2025 |
| Solar Radiation Forecasting | 10% reduction in hourly prediction errors | Enhances prediction over basic statistical models | Olcay et al., 2024 |
| Fault Detection and Diagnosis | Lower failure rates in ball joint fault detection | Better than human labeling in accuracy | Pérez-Cutiño et al., 2024 |
| Fault Detection and Diagnosis | Reduced downtime and costs in inspections | Superior to manual, sensor-based, or ROV methods | Zhang et al., 2024 |
| Fault Detection and Diagnosis | LCOE 44–85 $/MWhe through automation | Lowers O&M costs compared to traditional CSP | Bernehed et al., 2023 |
| Fault Detection and Diagnosis | 0.95 mIoU in segmentation | Outperforms PPLiteSeg and OCRNet | SuryaPrakash et al., 2024 |
| Fault Detection and Diagnosis | 92% fault classification accuracy, 30% faster response | Enhances reliability over manual inspections | Lu et al., 2023 |
| Fault Detection and Diagnosis | 15% maintenance cost reduction | Improves defect localization efficiency | Ghahremani et al., 2025 |

| | | | |
|---|---|---|---|
| Performance Optimization | Enhanced power output via SuDoKu reconfiguration | Better than static/dynamic methods for shading mitigation | Shrivastava et al., 2024 |
| Performance Optimization | 10-year durability, scalable production | Lower costs ($200–$400/W less) than III-V PV | Aponte et al., 2024 |
| Performance Optimization | 80% efficiency, 7.5g lift in solar-powered arms | More sustainable than conventional energy sources | Okokpujie et al., 2024 |
| Performance Optimization | Precise, repeatable SPS assembly | More efficient than single-robot or human methods | Wan et al., 2024 |
| Performance Optimization | 10.11% shorter trajectories in grasping | Improves over traditional Informed-RRT* | Yin et al., 2025 |
| Performance Optimization | 12% increase in energy capture | Optimizes tilt angles beyond static configurations | Gürfidan et al., 2025 |
| Performance Optimization | 20% increase in energy output | Enhances storage and peak shaving | Assareh et al., 2025 |
| Performance Optimization | 18% improvement in PCM-based systems | Superior thermal optimization | Li et al., 2025 |
| Robotic Maintenance and Monitoring | Stable motion in dust-removal | Outperforms conventional cleaning | Nguyen et al., 2025 |
| Robotic Maintenance and Monitoring | >96% navigation accuracy, 75-min operation | More efficient than manual cleaning | Munasinghe et al., 2024 |
| Robotic Maintenance and Monitoring | Up to 50% soiling loss mitigation | Better for large-scale plants than manual | Al Humairi et al., 2023 |
| Robotic Maintenance and Monitoring | Cost-reduced scalability in assembly | Less labor-intensive than manual | Carr et al., 2023 |
| Robotic Maintenance and Monitoring | 25% monitoring cost reduction | Improves over manual inspections | Kumar et al., 2018 |
| Robotic Maintenance and Monitoring | 10% increase in energy production | Enhances operational efficiency | Martinez-Gil et al., 2025 |
| Case Studies | 95.08% mAP0.5 in defect detection | 1.39% improvement over YOLOv8n | Zhao et al., 2025 |
| Case Studies | 99.91% precision in soiling classification | Optimizes cleaning over manual | Ahmed et al., 2025 |
| Case Studies | High accuracy in lunar assembly | Surpasses manual methods | Nunziante et al., 2025 |
| Case Studies | Real-time shaded panel detection | Enhances longevity over traditional monitoring | Shanthi Kumar et al., 2025 |

## 4. Discussion

The integration of artificial intelligence (AI) and robotics into solar photovoltaic (PV) systems marks a transformative shift in enhancing efficiency, reliability, and accessibility, as evidenced by the reviewed studies. This section critically evaluates these advancements, contrasting them with traditional methods, and employs a SWOT (Strengths, Weaknesses, Opportunities, Threats) framework to provide a comprehensive analysis of their potential and limitations. By synthesizing advancements, impacts, and challenges, this discussion underscores the revolutionary role of AI and robotics in solar energy while identifying critical areas for improvement.

## 4.1 Critical Evaluation of AI and Robotics Advancements

Solar Radiation Forecasting: AI-driven forecasting, particularly through Long Short-Term Memory (LSTM) networks, significantly outperforms traditional statistical models reliant on historical weather data, which often fail to capture solar radiation variability, leading to grid instability (Krishnan et al., 2023). LSTM models achieve a 10% error reduction in hourly predictions (Olcay et al., 2024) and an RMSE of 62 W/m² across 116 sites for short-term forecasts (Hu et al., 2025). However, their focus on short-term horizons (10 minutes to 4 hours) limits strategic planning in regions with unpredictable weather, unlike traditional models that, while less accurate, support longer-term forecasts (Krishnan et al., 2023). The computational intensity of LSTM models requires significant energy resources, potentially offsetting environmental gains in resource-constrained settings, a challenge not faced by simpler traditional methods.

Fault Detection and Diagnosis: AI and robotics, such as UAV-based deep learning and CNN-GAN frameworks, address high-error manual inspections by achieving 92% fault classification accuracy and 30% faster maintenance response (Lu et al., 2023; Pérez-Cutiño et al., 2024). These surpass human labeling and traditional sensors in accuracy and cost (Zhang et al., 2024). However, data dependency limits their effectiveness in underdeveloped regions, where datasets are scarce, unlike manual inspections that require minimal data but lack precision (Khorani et al., 2025). Potential biases in AI diagnostics, such as overfitting to specific panel types, risk misdiagnoses in diverse PV systems, are a concern that has been underexplored in studies.

Performance Optimization and Energy Storage: AI-driven optimization, including dynamic tilt adjustments and SuDoKu reconfiguration, enhances energy capture by 12–20% in regions like Turkey and Japan (Gürfidan et al., 2025; Assareh et al., 2025; Shrivastava et al., 2024). These outstrip static traditional PV systems, which are less efficient but universally deployable due to minimal customization needs (Li et al., 2025). Energy storage integration, such as compressed air systems, boosts output but is geographically limited and computationally demanding (Assareh et al., 2025). The limited focus on battery management highlights a gap, as traditional systems rely on established storage solutions with fewer integration challenges.

Robotic Maintenance and Monitoring: Robotic systems, including drones and LQR-controlled cleaners, reduce labor and costs by 25% and boost energy production by 10% compared to manual methods, which are impractical for large-scale farms (Kumar et al., 2018; Martinez-Gil et al., 2025; Nguyen et al., 2025). However, high upfront costs exclude small-scale operators, unlike manual cleaning, which is accessible but inefficient (Martinez-Gil et al., 2025). Scalability issues and maintenance needs for robotic hardware, such as drone battery life, may undermine long-term reliability compared to traditional labor-intensive approaches.

## 4.2 SWOT Analysis of AI and Robotics in Solar Energy

### *4.2.1 Strengths*

- Enhanced Efficiency and Precision: AI models, such as LSTM and CNN-GAN, improve forecasting accuracy by 10–14% and fault detection by 92% (Olcay et al., 2024; Lu et al., 2023), while robotic systems achieve navigation accuracy of over 96% in cleaning tasks (Munasinghe et al., 2024). These surpass traditional methods in grid stability and operational reliability.
- Cost Reduction: AI and robotics reduce maintenance costs by 15–25% and O&M expenses in CSP to \$44–\$85/MWh (Ghahremani et al., 2025; Bernehed et al., 2023), making solar energy more competitive with fossil fuels.

- Scalability for Large Systems: Robotic cleaning and multi-robot assembly systems enable efficient large-scale PV and SBSP deployments, outperforming labor-intensive traditional setups (Wan et al., 2024; Nagrale et al., 2024).
- Sustainability Alignment: AI optimizes land use by 15% and cuts CO2 emissions by 18% in CSP, aligning with global climate goals (Assareh et al., 2025; Gul et al., 2025).

*4.2.2 Weaknesses*

- Data Dependency**:** AI models require extensive datasets, which limits their effectiveness in regions with sparse infrastructure, unlike traditional empirical models (Khorani et al., 2025).
- High Initial Costs: Robotic systems and AI algorithms involve significant upfront investments, excluding small-scale operators, unlike affordable manual methods (Martinez-Gil et al., 2025).
- Computational Demands: LSTM and CNN models are energy-intensive, potentially offsetting environmental benefits, a concern less prevalent in simpler traditional systems (Balachandran et al., 2024).
- Geographic Specificity: Optimization models tailored to specific climates (e.g., Turkey, Japan) reduce universal applicability compared to broadly deployable traditional PV setups (Gürfidan et al., 2025).

*4.2.3 Opportunities*

- Long-Term Forecasting: Developing AI for extended predictive horizons can enhance strategic planning, surpassing the less accurate long-term forecasts of traditional models (Krishnan et al., 2023).
- Energy-Efficient AI: Optimizing algorithms to reduce computational energy use aligns AI with sustainability goals, addressing current study gaps (Balachandran et al., 2024).
- Scalable Robotics: Modular, cost-effective robotic designs could democratize access for small-scale farms, expanding market reach beyond traditional methods (Nawab et al., 2023).
- Data Scarcity Solutions: Hybrid models integrating AI with empirical data improve accuracy in data-scarce regions, supporting equitable adoption (Pérez-Rodríguez et al., 2024).
- Policy and Education: Subsidies and tax breaks reduce financial barriers, while culturally tailored education campaigns counter public skepticism, enhancing trust in traditional systems (Saleem & Abas, 2025; Seth, 2024).
- Workforce Retraining: Upskilling programs (59% of the workforce needs retraining, according to the WEF, 2025) strike a balance between job creation and displacement, fostering social acceptance.
- Lifecycle Assessments: Comprehensive environmental analyses of AI/robotic hardware mitigate ecological trade-offs, strengthening sustainability claims (Gul et al., 2025).

*4.2.4 Threats*

- Public Skepticism: Resistance to AI, driven by unfamiliarity or concerns about job displacement, could hinder its adoption, unlike traditional technologies that are trusted (Mudassir et al., 2024; Seth, 2024).
- Policy Instability: Reliance on subsidies increases the risk of disruption in unstable policy environments, a lesser concern for conventional financing (Saleem & Abas, 2025).
- Ecological Trade-offs: Unaddressed lifecycle impacts of robotic hardware (e.g., rare earth metals) could undermine environmental benefits, unlike simpler traditional systems (Kumar et al., 2018).
- Bias and Overfitting: AI models risk biases (e.g., overfitting to specific patient types), leading to misdiagnoses or inefficiencies, a challenge that is less prevalent in manual inspections (Khorani et al., 2025).

4.3. Addressing Challenges

The reviewed studies identify data scarcity, high costs, and public skepticism as key barriers to the adoption of AI and robotics in solar energy, with distinct implications compared to traditional systems (Khorani et al., 2025; Martinez-

Gil et al., 2025; Mudassir et al., 2024). Data scarcity hampers the effectiveness of AI in regions with sparse infrastructure, unlike less accurate but data-light traditional models. Hybrid models that integrate AI with empirical data achieve high accuracy in data-scarce regions; however, their scalability across diverse PV systems requires further testing (Pérez-Rodríguez et al., 2024). The high initial costs of AI and robotic systems exclude small-scale operators, unlike affordable manual methods, although subsidies and tax breaks, as seen in Pakistan, mitigate financial barriers (Saleem and Abas, 2025). Public skepticism, rooted in unfamiliarity and fears of job displacement, contrasts with trust in traditional technologies. Culturally tailored education campaigns and demonstrations of business success with AI can help build acceptance (Seth, 2024; Mudassir et al., 2024). Ethical considerations, such as addressing AI biases (e.g., overfitting risks) and ensuring equitable access for small-scale operators, are critical but underexplored, necessitating research into bias mitigation and inclusive deployment strategies to align with sustainable energy transitions (Zhou et al., 2021; Shaikh et al., 2023; Young et al., 2023).

4.4 Future Directions and Comparative Insights

AI and robotics offer superior efficiency and scalability compared to traditional solar systems, but addressing the associated gaps is crucial (Jha et al., 2017; Shaikh et al., 2023). Developing energy-efficient algorithms reduces computational demands, unlike traditional systems with simpler requirements (Balachandran et al., 2024). Expanding AI to long-term forecasting and diverse climates enhances versatility, surpassing static traditional setups (Krishnan et al., 2023). Lifecycle assessments of robotic hardware address ecological trade-offs, unlike conventional systems with minimal material impacts (Kumar et al., 2018). Workforce retraining and culturally sensitive outreach ensure inclusivity, aligning the benefits of AI with the accessibility of traditional systems (Saleem and Abas, 2025; Mudassir et al., 2024). Unlike static traditional setups, AI and robotics enable dynamic, high-precision solutions, but their success hinges on overcoming these challenges to realize their transformative potential.

## 5. Conclusion

In conclusion, the findings of this paper demonstrate that AI and robotics significantly enhance the efficiency and sustainability of solar energy compared to traditional systems. Still, their success depends on addressing computational, scalability, and social challenges. By leveraging the strengths of these technologies while mitigating their limitations, solar energy can solidify its role as a cornerstone of the global energy transition, surpassing the capabilities of conventional approaches. AI and robotics are revolutionizing solar energy, from precise forecasting to automated maintenance. These technologies drive environmental sustainability, economic growth, and social equity, making solar energy a cornerstone of the global energy transition. Despite challenges such as data scarcity and high costs, solutions like hybrid models and policy support offer a clear path forward. Policymakers, researchers, and industry leaders must invest in AI-driven innovations and workforce retraining in solar PV R&D to unlock the full potential of solar energy, ensuring a cleaner and more equitable future (WEF, 2025).

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